Title
Training a Large-Scale 3D Convolutional Neural Network Predicting Human Intelligence in Adolescent Brain Cognitive Development Study

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Background: Intelligence is complex, multi-dimensional, and encompasses a number of simpler cognitive processes and governed by the distributed brain circuitry. Literature shows the bran underpinnings of specific aspect of human intelligence; however, this knowledge has hardly led to a prediction of intelligence in an individual human. A promising, but untested, way to investigate the complex relationships between brain and cognition is the artificial intelligence-based data-driven approach with scalability. To test the feasibility of the deep neural network to the large-scale brain data, here we train several deep neural networks on the entire brain structural MRI dataset from the ABCD study in a task to predict fluid intelligence in pre-puberty children.

Methods: For the outcome label, we used fluid intelligence, estimated using the NIH Toolbox Neurocognition battery with confounding effects (e.g., site, sex, age, race/ethnicity, and maternal education) regressed out. The dataset consists of 3739 subjects in training set, 415 in validation set, and 4515 in test set. T1-weighted MRI were used as the input data. All the data come from the 2019 Medical Imaging Computation and Computer-Assisted Intervention (MICCAI) ABCD challenge (https://sibis.sri.com/abcd-np-challenge/).

We used two 3D-CNN architectures: Naive-CNN and ResNet50-3D. The Naive-CNN has 4 convolutional layers, followed by 2×2 max-pooling layers, ReLU layers, and dropouts.4 The 4 convolutional layers have output channels of sizes 10, 20, 40, and 80 respectively. Then, batch normalization is applied to the mini-batch. All the features from the last convolutional layer are sent to the 3 fully connected layers of sizes 4840, 2420, and 1. The ResNet50-3D architecture is derived from the well-known 2D ResNet-50 model with an added third dimension for the convolutional kernels. In total, the Naive-CNN model has about 527 million parameters and the ResNet50-3D model has about 47 million parameters.

To resolve the GPU memory issue owing to the high resolution 3D MRI, we used two parallel training paradigms: data parallelism (DP) and model parallelism (MP). In DP mode, the model is replicated onto 8 GPUs to which different mini-batch of images are fetched, so a total number of 24 images can

be consumed in a single run. In MP mode, we split the neural network model onto 4 GPUs, so that the input features to the 2nd GPU is the output features from the 1st GPU and so forth. MP mode allows an increased mini-batch size since the memory utilization of each GPU is significantly reduced. We ran our experiment using Cori HPC system at National Energy Research Scientific Computing Center (NERSC) and Google Cloud Platform (GCP). In Cori, we used 4 Nvidia Tesla V100 GPUs, each with 1530 MHz and 16 GB of memory, to experiment with the ResNet-50 3D model. In GCP, we used 8 Nvidia Tesla V100 GPUs to experiment with the Naive-CNN model.

Results: The performance metrics of the three neural network models on the validation set are: Naive-CNN Baseline, MSE (mean squared error),72.13; Naive-CNN Tuned, MSE, 71.51; and ResNet50-3D Baseline, 73.00. The baseline model does not include any pre-processing (i.e., normalization and log transformation). The tuned model includes both of the pre-processing steps along with hyperparameter tuning.

The overall magnitude of the training time – approximately 25-28 minutes per epoch – required for the Naive-CNN model shows that the task of predicting fluid intelligence scores from structural brain MRI can be achieved in a reasonable amount of time. Both versions of Naive-CNN surpass ResNet50-3D in model performance. The tuned version of the Naive-CNN demonstrates a competitive performance relative to the top-scoring model on the ABCD Challenge leaderboard (MSE=67.39).

Our training showed a monotonic decrease in the mean squared error of the Naive-CNN Tuned model throughout the iterative epochs of training. The mean squared error decreases from 398.37 in epoch 2 to 71.51 in epoch 8; it is clear that up to epoch 8, each shuffled iteration through the training set adds to the learning in the model.

The code for this 3D distributed deep learning framework, including the training, tuning, and testing scripts, can be found in the following GitHub repository:
https://www.github.com/ML4HPC/Brain_fMRI.git

Conclusions: Our study presents a novel application of data-driven AI approach to neuroscience. Our deep neural network trained on 3D brain structural MRI illustrates the feasibility in predicting human fluid intelligence estimated from multiple cognitive tasks. Using distributed deep learning framework on a GPU supercomputer, our framework successfully trained a deep neural network in approximately 4 hours. This scalability and feasibility may lead to more rigorous implementation of deep neural network in human developmental, cognitive, neuroscience research, such as developing an architecture optimized for human brain imaging data or integration of multiple modalities of MRI data to leverage both brain physiological and structural signals.
Future research encompasses two major endeavors: firstly, improving scalability by combining both data parallelism and model parallelism into the deep neural networks to maximize the use of all the GPUs in a node and to optimize the training time; secondly, applying model interpretabiltiy to make neuroscientific inferences as to what brain circuits and features are linked to human cognition and emotion in physiological or pathological/abnormal conditions.

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DISCLOSURE

Disclosure No, I have nothing to disclose.